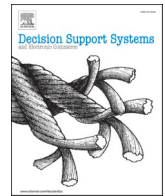




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The role you play, the life you have: Donor retention in online charitable crowdfunding platform

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ABSTRACT

Crowdfunding was first used by individuals and entrepreneurs to collect small-sized investments from crowds to support for-profit ventures, but now it is being touted as a valuable alternative to raise money for non-profit causes. Similar to various online settings, a key challenge for online charitable crowdfunding platform is the problem of donor retention. In this research, we disentangle donor retention behavior and build up a structural model to jointly examine donors' donation and latent attrition. By incorporating donation relationship and action related covariates into the model, we illustrate the drivers of donor retention and quantitatively examine their influence on individual donor's contribution and attrition activity. After calibrating the model with longitudinal donation transaction data from a leading charitable crowdfunding platform which enables teachers to request materials and resources for their classrooms, we find that (1) Teacher-donors (people who can be both donation makers and fundraisers) usually exhibit higher donation rate and lower attrition rate than normal donors on the platform; (2) Compared with site-donors (donors directly acquired through website visit), donors acquired through teacher referral usually have lower contribution and attrition rates; (3) The provided "charity gift card" and "donation matching offer" prosocial marketing programs on the platform seem to be a double-edged sword to donor retention. They have positive impact on donors' contribution rate, at the same time, they significantly increase donors' attrition rate; (4) Donors' initial contribution amount to the platform, successful donation result and "Thank-You" feedback from fundraisers can significantly decrease their attrition rate. Our results provide insights on new donor acquisition and donor relationship management in online charitable crowdfunding market.

1. Introduction

Online crowdfunding was first used by individuals and entrepreneurs as an innovative financial service to attract small-sized investments from crowds to support for-profit ventures through the Internet [13,23,35,52]. Now, it is being touted as a valuable tool to raise money for philanthropy [21]. For example, to fight with the COVID-19 pandemic, more and more financially stable individuals and organizations are turning to kinds of charitable crowdfunding platforms to help thousands of people and small business all over the world who are affected by the coronavirus. Two leading and independent non-profit crowdfunding platforms in the United States, *DonorsChoose.org* and *GoFundMe.org*, have raised more than \$70 million from the crowds within several weeks after the outbreak of COVID-19. The collected

money is widely used to support students and unemployed workers in poverty, to purchase personal protective equipment for health-care workers, and to cover personal unforeseen medical expenses. Generally speaking, online charitable crowdfunding allows donors to support their most desired charitable causes and designate the beneficiary of their fund rather than letting the nonprofit distribute the fund to the recipients. This highly efficient preference match results in a higher value of the charitable contribution [25,47].

However, in practice there are several issues plaguing the development of online charitable crowdfunding market. One of the critical challenges is donor retention, defined as the problem of keeping attracted donors interested and engaged so that they can continue to make donations year after year. Many extant studies and reports show that the average donor retention ratio in charitable market between

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2005 and 2018 is around 44.6%,² that number for the first time donors in online charitable platforms is only around 25% [3,5]. As such, improving donor retention performance has become an imperative task for each charitable crowdfunding platform, and tremendous fundraising effort has already been made to turn one-time donors into repeated donors [20]. For example, old donors or fundraisers are encouraged to solicit new donors, and individuals or organizations who benefit from donations are suggested to provide positive feedbacks (such as sending a “Thank-You” letter or packet) to the donors [3]. Since donors who participate in charitable crowdfunding will never receive any repayment, some innovative and prosocial marketing programs such as “charity gift card” and “donation matching offer”³ are provided to acquire more new donors and attract more donations from old donors. For instance, between January 2001 and October 2016, *DonorsChoose.org* has issued more than 1,053,024 charitable gift cards with various values, and more than 27.57% projects on the platform have been provided with all kinds of matching offers.

Although the aforementioned actions are widely adopted in online charitable crowdfunding practice, very limited theoretical attention has been paid to examine their impact on donor retention. The majority of extant online charitable crowdfunding studies mainly focus on exploring the drivers of donation decision and antecedents of successfully funded projects (we refer to the next section for a complete review). Many donor-related factors (e.g., donor identity [20]) and donation experiences related factors (e.g., donors’ experiences with “charity gift card” [28,37] and “donation matching offer” [24]) are verified to have significant impact on donors’ contribution intention or projects’ fundraising performance, while their influences on individual donor’s retention have not been carefully investigated [3,55]. Much knowledge about online donor retention comes from the experiences of professional platform managers, lab experiments and online donation survey [9,39]. They do help to shed some light on donor retention behavior, but one notable limitation of those actions is that they usually use cross-sectional survey data to measure donation intention related variables at the same point in time. This usually results in bias from common method variance [32] and carryover and backfire effects [8]. Furthermore, donors’ donation and attrition behavior are separately examined in those studies. This is usually inconsistent with the real operation of charitable crowdfunding in which donors’ contribution decision and latent attrition decision in online charitable crowdfunding platform are usually correlated.

Building on this research gap, we analyze the granular donation transaction data in the charitable crowdfunding platform of *DonorsChoose.org* to quantitatively investigate the impact of donor and donation experiences related factors on donor retention. Our study is designed to answer the following two research questions: (1) Whether donor and donation experiences related factors in charitable crowdfunding platform affect their retention? (2) If so, how do those factors affect their retention behavior?

To answer these research questions, we decompose donor retention into two decision processes that a typical donor usually goes through: (i) donation process, and (ii) latent attrition process, or when to become permanently inactive. Then we build up a structural model to jointly model both donors’ contribution behavior and attrition behavior. To improve the proposed model’s flexibility in fitting real operation scenarios in online charitable market, we allow donors’ contribution rate (or donation rate, hereafter we use them interchangeably) and their

latent attrition rate to (or dropout rate, hereafter we use them interchangeably) be correlated. Furthermore, to illustrate what factors will significantly affect donors’ contribution and attrition rates, we link donation relationship and action related covariates to their contribution and attrition behavior (more discussion can be found in Section 3.2). The proposed model is calibrated with a unique longitudinal donation transaction data of different donor cohorts and the robust empirical findings show that: (1) Teacher-donors (people who can be both donation makers and fundraisers) usually exhibit higher donation rate and lower attrition rate than normal donors on the platform; (2) Compared with site-donors (donors directly acquired through website visit), donors acquired through teacher referral usually have lower contribution and attrition rates; (3) Donors’ experiences with the prosocial programs provided by the platform (e.g., “charity gift card” and “donation matching offer” programs) seem to be a double-edged sword to donor retention. They have positive impact on donors’ contribution rate, and at the same time, they significantly increase donors’ attrition rate; (4) Donors’ initial donation amount to the platform, initial donation result and donation feedbacks from fundraisers can significantly decrease donors’ attrition rate, but have no significant impact on donors’ donation rate.

Overall, this study contributes to extant literature and practice on charitable crowdfunding in several ways. First, we provide a holistic model to illustrate online donors’ retention problem, which is one of the most fundamental issues for both online charitable crowdfunding platforms and offline non-profit organizations. In the proposed model, donors’ contribution rate and latent attrition rate are allowed to be correlated. This improves model’s flexibility in fitting online donation scenarios wherein donors’ contribution rate and attrition rate are not independent of each other. Second, by including both donation relationship and action related covariates into the proposed model, we quantitatively investigate the heterogeneity of donors’ both contribution rate and latent attrition rate. We are able to provide insights on what factors will significantly influence donors’ donation and attrition behavior separately. To the best of our knowledge, this is our original contribution. Third, from the perspective of managerial practice, we provide a quantitative method to examine online donors’ both contribution and attrition rates. It suggests what factors are important in affecting donors’ contribution and attrition, and in return provides platform managers as well as owners in offline non-profit organizations with executable suggestions on new donor acquisition and donor relationship management decisions.

The remainder of this paper is organized as follows. In Section 2, we review related works and describe the research gap. In Section 3, we introduce our research context, data set, conceptual model and variable construction. Section 4 discusses the empirical model and Section 5 reports the estimation results. We assess the robustness of our findings in Section 6. In Section 7, we conclude our study by discussing the theoretical and practical implications, and point out directions for future research.

2. Related works

2.1. Online charitable crowdfunding

As an innovative financial service, online crowdfunding was first used by individuals and entrepreneurs through the Internet to attract small-sized investments from crowd to support for-profit ventures [13,23,35,52]. Now, it is being touted as a valuable tool to collect money for charity needs. Generally speaking, online charitable crowdfunding usually follows a patronage model, in which donors function as philanthropists [27] and they will never receive any monetary returns. As such, some initial studies begin to explore donors’ motivation and behavior in this market. They pointed out that funders’ intrinsic motivations (i.e., personal interest, beliefs, empathy, social influence and social trust) as well as their extrinsic motivations (i.e., improving social problems and knowledge) are two main drivers for their donation

² <https://bloomerang.co/retention>, accessed on April 7, 2020.

³ The “charity gift card” program in online charitable crowdfunding allows donors to purchase and share the donation gift card. It can be directly used to support any projects posted on the platforms if the card holder like. The “donation matching offer” program is able to offer additional donation amount for every dollar that donors give to projects which are satisfied some predetermined requirements.

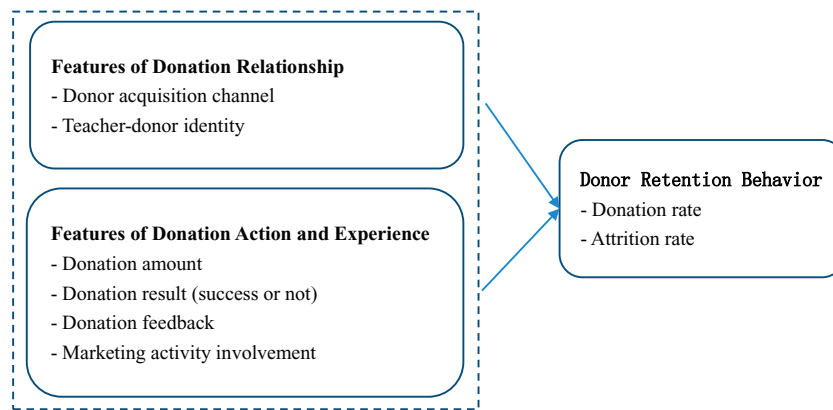


Fig. 2. The Conceptual Model of Donor Retention.

actions [4,7].

With the rapid development of online charitable market, more and more attentions have been paid to the antecedents of successfully funded projects. Some studies within this stream pointed out that the credibility of fundraisers, projects' quality and popularity, fundraising information transparency [25], donor identity [20] as well as the social influence from social media platforms [2,47] in online charitable market can significantly affect online donors' contribution intention and projects' fundraising performance. Authority certification from third party also can help fundraisers collect the money they need [25,31]. With the widely use of many prosocial marketing programs such as "charitable gift card" and "donation matching offer", some researches begin to explore their impacts on donors' contribution behavior and projects' fundraising performance. For example, Meer [24] examined the extent to which matching grants for donations to certain requests affect giving to others on *Donorschoose.org*. These empirical findings indicate that the provision of "donation matching offer" does not appear to crowd out giving to projects. The role of charitable gift card in charitable market is also examined by Mulder and Joireman [28] and it is verified to be able to encourage donors' donation.

Recently, some researchers begin to develop useful tools to help fundraisers improve their fundraising performance. For example, Li et al. [21] proposed a recommendation mechanism for online charitable crowdfunding by fully utilizing donors' preferences, their relationship with fundraisers, as well as fundraising dynamics. It can effectively match donors with projects and significantly improve projects' fundraising success rate. Song et al. [45] built a structural econometric model of utility-maximization to recommend donors with fundraising campaigns on *Donorschoose.org*.

According to the aforementioned studies, we can easily find that donor and donation experiences related factors, such as donor identity, donation experiences with charity gift card and matching offer, have been found to have significant impact on their donation motivation and projects' fundraising performance. However, their impacts on donor retention have not been carefully investigated [3,55]. As a supplement to extant research, we quantitatively examine the potential impact of donation related factors on donor retention behavior.

2.2. Donor retention in charities

Our work is also related to the large body of literature that investigates donor retention in charities. In reality, donor retention is all about focusing on existing donors and finding creative solutions and engaging ways to turn them into repeated and loyal donors [37,41,55]. Since the cost of acquiring a new donor is usually higher than that of retaining an existing one and it is able to reflect donor satisfaction [44], donor retention has become a very important issue for non-profit organizations.

In the past several years, researchers have identified many factors related to donor retention in traditional offline setting. For example, Schweidel and Knox [43] indicated that direct marketing from fundraisers will increase donation incidence for active donors, while it has the potential to increase a donor's attrition rate. Some empirical findings from survey and experiment data set pointed out that a positive acknowledgement and feedback from people who benefit from donations is very important to decrease donors' attrition rate [6,26]. Furthermore, the content analysis of direct-email and other marketing activities target at donors suggested that (1) personalization email to potential donors who share a similar surname with fundraisers [29], (2) emphasizing fundraisers' preparedness and training efforts for the fundraising projects, and (3) including small cards that affirm donors' identity [37] usually have positive impacts on donors' contribution and retention. When writing soliciting emails to donors, fundraisers should use more emotional arguments than logical arguments [34]. Other important factors including relationship management, trust, donors' satisfaction and involvement are also found to have different effect on donor retention [30,38,40].

In contrast to traditional charities, online charitable crowdfunding has several distinctive features: (1) In online charitable crowdfunding, fundraising projects are usually initiated by individuals rather than nonprofit organizations [14]; (2) The posted projects or campaigns often focus on specific and size-limited charity causes [22]. This requires donors' constant effort to identify and support needed projects; (3) Besides marketing email, more prosocial marketing programs are provided by online charitable platforms to solicit more contributions from donors, such as charity gift card [28,37] and matching offer grants [24]; (4) Finally, fundraisers can provide real-time update on their fundraising process and conduct more frequent interactions with potential donors through the conversation functions provided by online charitable crowdfunding platforms [47,50]. The new features and the enormous charitable causes offered in the online crowdfunding platforms usually impose high search and transaction costs because donors are usually required to spend time and effort searching for their most desired ones. As such, it renders the challenges of donor acquisition and retention. To cope with this challenge, many studies begin to provide knowledge about online donor retention through conducting lab experiments or online donation survey [9,39]. One notable limitation of extant survey studies is that they usually use cross-sectional survey data to measure the donation intention related variables at the same point in time. This usually results in bias from common method variance [32] and carry-over and backfire effects [8]. Furthermore, donors' donation and attrition behavior are usually separately examined in those studies. This is usually inconsistent with the real operation of charitable crowdfunding in which donors' contribution decision and latent attrition decision are usually correlated.

Recently, some emerged studies begin to conduct quantitatively

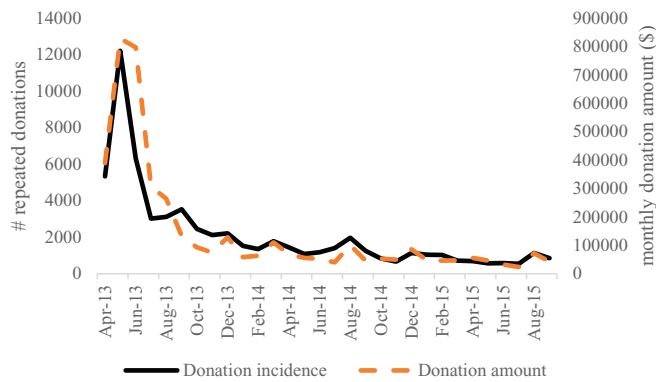


Fig. 1. Observed Donation Behavior for Donor Cohort.

analysis to examine online donor retention. For example, Zhao et al. [55] proposed a joint deep survival model to jointly predict individual donors' donation recurrence and retention. Zakhlebin and Horvát [53] used survival analysis model to explore how investment decisions affect investors' retention on equity crowdfunding platform. By making full use of the features extracted from the perspectives of donors, fundraisers and crowdfunding projects, Althoff and Leskovec [3] built many standard machine learning techniques to predict online donor retention. They found that a logistic regression model using all features can achieve the best prediction performance. Consistent with extant literature in this stream, we also focus on donor retention topic. Different from them, we illustrate the drivers of donor retention behavior and quantitatively examine their influence on individual donor's contribution and attrition activity. Specifically, we disentangle donor retention behavior by decomposing it into two key decision processes that a typical donor goes through: (i) donation process, and (ii) latent attrition process, and build up a structural model to jointly model both donors' contribution behavior and attrition behavior. To improve the proposed model's flexibility, we allow donors' contribution rate and their latent attrition rate to be correlated and can be affected by both donor and donation experiences related covariates. Therefore, our study enriches extant works on donor retention. The proposed model can also be generalized to a broader area of customer retention in other online settings.

3. Research context, data and variables

3.1. Research context

Our research data comes from *DonorsChoose.org* (hereafter we use *DC.org*). It is a United States-based online nonprofit organization that allows individuals to donate directly to public school classroom projects. *DC.org* was founded in 2000, and Charity Navigator gives it the highest rating every year since 2005. By the end of March 2020, more than \$0.9 billion dollars has been raised for more than 1.6 million projects, covering 84% of public schools and 39 million students in America. Through *DC.org*, teachers are able to request materials and resources for their classrooms (they can compose and post a short essay on their students, project plans and itemize needed materials on *DC.org*) and make these project requests available to individual donors. Donors can give \$1 or more to projects that interest them, and then *DC.org* will purchase necessary supplies and ship them directly to the schools. Every project contains a line-item budget and a description of the project. Donors might be able to receive photographs of the project taking place in the classroom and a letter from the teacher. It should be noted that, teachers can play two roles on *DC.org*. On the one hand, they can be fundraisers through posting crowdfunding projects for their students. On the other hand, they can become donors (we call them teacher-donors) through making contribution to other teachers' crowdfunding projects. The operations of *DC.org* are 100% supported by optional

Table 1

Descriptive statistics of the selected donor cohort.

Descriptive statistics (Donation transaction level)	
# Observations	70,441
# Donors	9255
Mean Observation Per Donor	7.61
Average Amount Per Donation	\$ 66.73
Average Amount Per Donor	\$ 507.90

donations from donors.

Similar to many extant charitable crowdfunding platforms, two common prosocial marketing programs named “charity gift card” and “donation matching offer” are provided on *DC.org* to attract more new donors and encourage more donation from old donors. Through “charity gift card” program, donors on the platform are able to purchase *DonorsChoose* gift card as a gift of giving. The gift card is 100% tax deductible and can be shared with donors' friends and family. All the gift card recipient can contribute to the posted projects on *DC.org* by using the credit in the card. To facilitate the operation of “donation matching offer” program, there are a number of foundations and corporations partner with *DC.org* to provide matching grants for projects satisfying some criteria. Teachers who propose the project can apply for these offers and obtain subsidies for their objective amount. For every dollar a donor gives to the matched project, additional money, which is usually proportional to the donor's contribution, will be given as well by the matching grants. All the projects with matching offers can be recognized through an obvious mark on the website. The provided matching offers usually come in two categories named “Double Your Impact” (i.e., *DYI*) matching offer and “Almost Home” (i.e., *AH*) matching offer. The former offers a standard dollar-for-dollar linear match for matched projects and the later provides all but the last \$100 of funding to the matched project.

Overall, the tractable donation process and rich donation interactions on *DonorsChoose* make this platform become a promising context to explore online donor retention behavior in our study.

3.2. Data summary

We collect the data from *DC.org* when it is operationally stable. More specifically, our data includes detailed information about all individual donors who made their first-ever donation in the second quarter of 2013 and had at least one donation record through September 2015 (in our robustness analysis section, we track the behavior of donor cohorts who come from the first and third quarter of 2013, respectively).

The collected data comprises 9255 donors who have collectively made 70,441 donations and \$ 4,700,641 donation amount to 39,075 unique fundraising projects during the considered time period. For each donor, we have her/his donor id and identity (i.e., whether the donor is a teacher-donor or not). For each donation made by a given donor, we have the donation id, timestamp, amount to the selected project, payment method (whether the donation is paid through web purchased gift card or not), whether the donation is teacher referred or not, the final fundraising result of the supported project (i.e., it is successful or not) and whether the donor received a “Thank-You” packet after the donation. For each donated project, we also collect its listing features such as release date, fundraising target, project description, whether the project is qualified for “donation matching offers”, and so on.

Table 1 provides some descriptive statistics of donors' contribution activities at donation transaction level. On average, a donor makes 7.61 donations and contributes \$ 507.90 to projects posted on *DC.org* during our sample period, and the average amount for each donation is \$ 66.73.

Fig. 1 illustrates the repeat donation activity from the tracked donor

cohort. Consistent with the serious donor attrition fact reported in the practice of online charitable crowdfunding market,⁴ we see that the number of monthly total donation declines from 12,206 in the early stage to 846 in our final sample period. The total monthly donation amount also shows a very similar decline pattern, which drops from \$ 828,601.57 to \$42,092.17. In the following, we construct variables to guide our empirical analysis.

3.3. Conceptual development and variable construction

Previous studies on customer retention have extensively examined the drivers of individual's retention behavior, and among which loyalty is believed to be one of the most important factors [46,49]. Moreover, customer loyalty is believed to consist of two components: attitudinal part and behavioral part. The former captures individual's intention to rebuy and recommend, and the latter describes actual usage and retention behavior [10,36]. Customer trust, short-term promotion and marketing activities (for example loyalty programs) and service quality are all found to be the antecedents which can significantly influence loyalty and retention [11,46,48,49]. The focus of our research is on examining the impact of a broader set of characteristics of donor's actual donation on their retention behavior. We propose that donor retention is build up donor's loyalty and trust toward the platform, and it can be affected by two broad sets of factors: features of donation relationship and features of donation action and experience (see Fig. 2). In the first set, we consider how the donor-platform relationship started by looking at the channel of donor acquisition (whether the donor was acquired from teacher referral or website visiting). That is because referred customers has been verified to have a stronger relationship with the platform in the long run [42]. In addition, we also look at donor' teacher identity in the platform, as teacher-donors can be both donation makers and fundraisers. The "dual role" they played may strength their relationship with platform. Within the second set, we examine four features of real donation action and experience: donation amount, donation result, donation feedback and marketing activity involvement. These observable features may reflect and cultivate individual donor's trust to the platform and finally influence their retention behavior. Fig. 2 summarizes the conceptual model of donor retention, and we will discuss these factors as well as relevant variable construction in more detail next.

3.3.1. Donor acquisition channel

Extant literature on the loyalty behavior of referred customers in online store argue that new customers who are acquired from the referral of old customers usually exhibit higher commitment and attachment. That is because the referral of old customers may increase person's trust and emotional band with the store [42]. What is more, the referral may help to mitigate new customers' perceived risk of purchasing online and increase their willingness to buy [18]. Similarly, if all else being equal, we argue that for donors who are acquired from teacher referral in DC.org, there is a transference of the referrer's positive and trust attitudes to the receivers. This is going to mitigate new donors' perceived risk of donation online and increase their willingness to make donation. In comparison, donors directly acquired through website visit (i.e., site-donors) may have lower commitment and attachment. Thus, to test this hypothesis, we construct the acquisition channel variable, *IsTeacherReferral_i*, from the data, and incorporate it into our empirical model to examine its impacts on donors' retention behavior.

3.3.2. Donor identity

In addition to donor acquisition channel, teacher-donor identity is

also very important in our research context. The studied platform is for teachers to request materials and resources for their classrooms, thus there are usually two types of donors: normal donors and teacher-donors. The former are general project supporters on the platform, while the latter are a group of supporters who can be both donation makers and project fundraisers. Thus donors' teacher identity becomes an eye-catching part on the platform. Existed research on offline donation behavior show that disclosing donors' identity information usually has positive impacts on their contribution and retention [37]. Many studies on online crowdfunding market also found that fundraisers who receive funding from others may feel obliged to support by giving back (Colombo et al. [12,56]). In our research context, the "dual role" played by teacher-donors may trigger their feeling of obligation to support crowdfunding projects posted by other teachers. In this case, teacher-donors may become more active on the platform. In other words, if all else being equal, we expect teacher-donors in our study exhibit different retention behavior compared with normal donors. To test this hypothesis, we construct *DonorIdentity_i* to capture donor *i*'s identity (i.e., normal donor or teacher-donor) and incorporate it into our empirical model to examine its impacts on donors' retention behavior.

3.3.3. Features of donation action and experience

Donors' donation amount to the platform as well as their marketing activity involvement may directly reflect their trust to the donation platform. The donation results and feedbacks from fundraisers provide them with the possible feeling of altruism when helping others. Both of them may further affect donors' retention behavior. In this study, we focus on the possible impacts brought by donors' initial donation action and experience because they can be easily achieved and used to examine donor retention in the normal course of fundraising practice. Moreover, from theoretical perspective, many psychology and economic literature have emphasized the importance of "the first impression or experience" in human relationships with many social circumstances [33]. For example, Xiang and Fesenmaier [51] found that information searchers with favorable first impressions toward a webpage are more likely to stay on the website and use it for trip planning. Evans et al. [15] pointed out that the first impression of a customer is able to affect the effectiveness in an initial sales encounter. Similarly, in the online charitable crowdfunding platform, donors' initial donation action and experience may also play a vital role in affecting their future activates such as repeated donation and attrition. To well understand their impacts, we construct some relevant variables including donors' initial donation percentage to DC.org (e.g., *DonPercentToDC_i*), their involvements in marketing programs like "charity gift card" and "donation matching offer" (e.g., *PaidbyGiftCard_i*, *DYIMatchingOffer_i*, and *AHMatchingOffer_i*), their first-time donation result (e.g., *FundRaisingResult_i*) and whether they received a "Thank You Packet" from their first donation or not (e.g., *IsThankUPacketRec_i*).

Table 2 summarizes the explanations and descriptive statistics for those constructed variables.

4. Model development

Before developing the model, we first use Fig. 3 to illustrate donors' contribution activities on *DonorsChoose* platform. Suppose a donor *i* has made ($J + 1$) donations on the platform at ($t_0, t_1, t_2, \dots, t_j$) over our observed data period (T_{end} refers to our observation end time point, September 30th, 2015). Since we can't observe donor *i*'s real registered time on the platform, we assume her life time starts at t_0 (when the first donation occurs) and track her donation activities until time T_{end} . Next, we propose our model to describe donor *i*'s repeated contribution behavior and attrition behavior over time (t_0, T_{end}).

4.1. Donation rate

Following previous literature on customer retention analysis

⁴ <http://afpfep.org/wp-content/uploads/2018/04/2018-Fundraising-Effectiveness-Survey-Report.pdf>

Table 2
Descriptive Statistics of Donors' First-time Donation Activities.

Variable name	Explanations	Max	Min	Mean	Std.
Donor relationship: <i>DonorIdentity_i</i>	Whether donor <i>i</i> is a teacher-donor or not (1 = yes)	1	0	0.19	0.39
<i>IsTeacherReferral_i</i>	Whether donor <i>i</i> is acquired from teacher referral or not (1 = yes)	1	0	0.30	0.46
Donation action and experience: <i>DonPercentToDC_i</i>	Percentage of donor <i>i</i> 's first-time donation amount which are contributed to support DC.org	1	15	1.40	2.23
<i>PaidbyGiftCard_i</i>	Whether donor <i>i</i> 's first-time donation is paid by gift card or not (1 = yes)	1	0	0.11	0.32
<i>DYIMatchingOffer_i</i>	Whether donor <i>i</i> 's first-time donation is matched by "DYI" match offer or not (1 = yes)	1	0	0.13	0.34
<i>AHMatchingOffer_i</i>	Whether donor <i>i</i> 's first-time donation is matched by "AH" match offer or not (1 = yes)	1	0	0.03	0.18
<i>FundRaisingResult_i</i>	Whether donor <i>i</i> 's first supported project is successful or not (1 = yes)	1	0	0.86	0.35
<i>IsThankUPacketRec_i</i>	Whether a donor received the <i>Thank You Packet</i> from her first donation or not (1 = yes)	1	0	0.10	0.30

Notes: Statistics are computed using raw values.

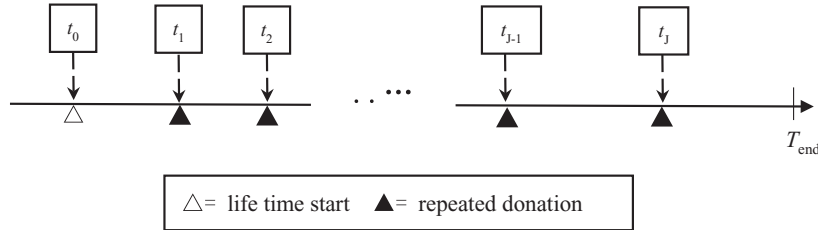


Fig. 3. Illustration of a Donor's Contribution Sequence.

[16,17], we assume that while donor *i* is active on *DonorsChoose*, her inter-donation time span between any two consecutive donations is exponentially distributed with λ_i .⁵ In probability theory and statistics, the exponential distribution is the probability distribution of the time between events in a Poisson point process. That is to say, we actually use a stochastic Poisson process to model donor *i*'s donation activities and the λ_i can be treated as donor *i*'s donation rate (i.e., the average number of donation activities within a fixed time period on *DC.org*). Given the exponential distribution and donation rate λ_i , the probability density function for donor *i*'s inter-donation time between the *k*-th and (*k* + 1)-

th donation occurring at t_k and t_{k+1} can be written as follows:

$$f(t_{k+1}|t_k) = \lambda_i \exp(-\lambda_i(t_{k+1} - t_k)) \quad (1)$$

Similarly, the probability function that donor *i* remains active but makes no donation in the right-censored time period (t_{ji} , T_{end}] (i.e., donor *i*'s survival function) can be written as follows:

$$S(T_{end}|t_j) = \lambda_i \exp(-\lambda_i(T_{end} - t_j)) \quad (2)$$

The parameter λ_i in both Eqs. (1) and (2) is used to capture donor *i*'s heterogeneous donation rate, and it is assumed to follow a log-normal distribution (The log-normal distribution is able to ensure that the donor's donation rate is non-negative, and widely used in previous studies). In order to capture the effect of donors' profile characteristics and first-donation experiences on their donation rate, we model the mean of $\log(\lambda_i)$ as a linear regression of covariates of interest. The function can be written as follows (we use subscript *i* to emphasize the donation rate is for donor *i*):

$$\log(\lambda_i) = \mu_{\lambda_i} = \alpha_0 + \alpha_1 X_i + \varepsilon_i \quad (3)$$

In Eq. (3), X_i is a vector including *DonorIdentity_i*, *IsTeacherReferral_i*, *DonPercentToDC_i*, *PaidbyGiftCard_i*, *DYIMatchingOffer_i*, *AHMatchingOffer_i*, *FundRaisingResult_i* and *IsThankUPacketRec_i*. They describe donor *i*'s identity, how donor *i* is acquired, and her initial donation experiences on the crowdfunding platform. α_0 - α_8 are coefficients to be estimated. They capture the effect of corresponding variables on donors' donation rate. ε_i is an error term following normal distribution with mean 0 and variance σ_{λ}^2 . It is able to capture the random shocks to the donation rate.

4.2. Latent attrition rate

Since donors may become inactive after making a donation, but this is not directly observable to both platform managers and researchers. To model this unobservable attrition behavior, we introduce donors' latent attrition rate in our model. Following previous studies on consumer attrition [1,16,43], we assume that the possibility that donor *i* becomes

inactive after a donation is γ_i and it is also assumed to follow a log-normal distribution. In order to capture the effect of donors' observable characteristics such as identity, acquisition channel and initial donation experiences on their attrition rate, we model the mean of $\log(\gamma_i)$ as a linear regression of covariates. The function can be written as follows (we use subscript *i* to emphasize that the dropout rate is for donor *i*):

$$\log(\gamma_i) = \mu_{\gamma_i} = \beta_0 + \beta_1 X_i + \zeta_i \quad (4)$$

In Eq. (4), X_i is a vector containing the same variables as we described in Eq. (3). β_0 - β_8 are coefficients to be estimated. Similarly, they capture the effect of corresponding variables on donors' attrition rate. ζ_i is an error term following normal distribution with mean 0 and variance σ_{γ}^2 . It is able to capture the random shocks to the attrition rate.

Obviously, a donor's donation rate and attrition rate are not independent because they are simultaneously determined by the same set of donation related covariates. To allow for the possible correlation

⁵ To make sure this assumption is reasonable in our study, we have examined the regularity of donors' intertransaction times in our data. The estimated values of regularity parameter *k* through different methods are very close to 1. This supports the assumption of exponentially distribution of donors' inter-donation times.

between donation rate and latent attrition rate, we assume donor i 's donation rate λ_i and dropout rate γ_i are correlated. To describe this correlated relationship in our proposed model, the two error terms in Eqs. (3) and (4) are assumed to follow a multivariate normal distribution with mean $[0,0]$ and covariance matrix Σ . As such, we can put Eqs. (3) and (4) together and describe the compact equation system as follows (we use subscript i to emphasize the donation rate and dropout rate are for donor i):

$$\begin{bmatrix} \log(\lambda_i) \\ \log(\gamma_i) \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_{\lambda_i} \\ \mu_{\gamma_i} \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_{\lambda}^2 & \delta_{\lambda\gamma} \\ \delta_{\lambda\gamma} & \sigma_{\gamma}^2 \end{bmatrix} \right) \quad (5)$$

In Eq. (5), μ_{λ_i} and μ_{γ_i} are the mean of $\log(\lambda_i)$ and $\log(\gamma_i)$, respectively. The correlated coefficient between donation rate and dropout rate can be calculated based on the covariance matrix Σ .

4.3. Likelihood function

Given donor i 's donation rate and attrition rate, the likelihood of observing her first repeated donation occurring at time t_1 (see Fig. 2) is $\lambda_i e^{-\lambda_i(t_1-t_0)}$, and the likelihood of her second repeated donation occurring at time t_2 is the probability of donor i remaining active at time t_1 times her donation probability at time t_2 , which is $(1 - \gamma_i)\lambda_i e^{-\lambda_i(t_2-t_1)}$. Similarly, the likelihood of the k -th repeated donation occurring at time t_k is the probability of donor i remaining active at time t_{k-1} times her donation probability at time t_k , which is $(1 - \gamma_i)\lambda_i e^{-\lambda_i(t_k-t_{k-1})}$. Finally, the likelihood of observing zero donation between time $(t_j, T_{\text{end}}]$ is a summarization of two parts: (1) the probability of donor i becomes inactive at time t_{j+1} , which is γ_i ; and (2) the probability of donor i still remains active but she makes no donation during $(t_j, T_{\text{end}}]$, which equals $(1 - \gamma_i)e^{-\lambda_i(T_{\text{end}}-t_j)}$. As a result, the probability of observing donor i 's J repeated donations on DC.org platform within the observed time period (i.e., $[t_1, T_{\text{end}}]$) can be written as follows:

$$L_i(\lambda_i, \gamma_i | t_1, t_2, \dots, t_J, T) = \lambda_i e^{-\lambda_i(t_1-t_0)} (1 - \gamma_i)\lambda_i e^{-\lambda_i(t_2-t_1)} \dots (1 - \gamma_i)\lambda_i e^{-\lambda_i(t_J-t_{J-1})} \cdot$$

$$[\gamma_i + (1 - \gamma_i)e^{-\lambda_i(T_{\text{end}}-t_J)}] \quad (6)$$

Hence, the overall likelihood of observing all donors' repeated contributions within our sample period can be written as follows:

$$L = \prod_{i=1}^N \int L_i dF(\lambda_i, \gamma_i) \quad (7)$$

where N is the total number of donors, and $dF(\lambda_i, \gamma_i)$ refers to the probability density function of the correlated distribution for donation rate λ_i and dropout rate γ_i .

The benefits of the proposed model are two folds. On the one hand, it has greater flexibility to fit the scenarios wherein donors' donation decision is correlated with their attrition behavior. On the other hand, some donation related variables can be linked with contribution and attrition rates through our model. This can help to illustrate what factors will significantly influence donors' donation and attrition and in return provide platform managers with many insights on how to conduct new donor acquisition and donor relationship management.

5. Estimation and empirical results

In this section, we report and discuss our empirical findings through two subsections that pertain to our earlier description.

5.1. Computation and estimation

In our model development, we relax the independence of donors' donation process and latent attrition process by allowing them to be correlated. Furthermore, our model is allowed to incorporate donors' covariates such as donors' identity, acquisition channel and initial

donation experiences to interpret their donation and attrition rates. This provides greater flexibility to our model. However, those two extensions complicate the model and we can hardly derive a closed-form solution for the model estimation. That is to say, it would be very difficult for us to estimate the proposed model efficiently via means of maximum likelihood estimation if we want to simultaneously consider the correlated-relationship between donation rate and attrition rate, as well as their heterogeneity brought by covariates at individual level. To better solve this problem, we take the advantage of Bayesian approach and use the Markov Chain Monte Carlo (MCMC) method. The Bayesian approach with MCMC allows for more flexible assumptions in the model to be estimated (e.g., the correlated-relationship between donation rate and attrition rate as well as their heterogeneity brought by covariates at individual level). Moreover, it can provide richer estimation results. In our case, this method can estimate the marginal posterior distributions of the parameters used in our model rather than point estimates. It is able to report individual-level parameter estimates for donors' donation and attrition behavior.

The Bayesian approach with MCMC method can be easily executed in R with the help of a publicly available package named "Bayesian Tools".⁶ Following the standard process when using Bayesian estimation method [1,19,54], we first assign non-informative priors to the parameters to be estimated. Specifically, the prior density for both λ_i and γ_i is chosen to be log-normal. For coefficients $\alpha_0, \alpha_1, \dots, \alpha_8$ and $\beta_0, \beta_1, \dots, \beta_8$ in Eqs. (3) and (4), we use multivariate normal prior. For covariance matrix Σ , we assign an inverse Wishart prior. After that, we employ sample draws generated from MCMC chain to calculate summary values of model fit and parameters to be estimated. The MCMC steps are repeated for 7000 iterations, with a burn-in period of 3500 iterations. The trace plots of all the estimated parameters are displayed in Fig. 4. A visual monitoring on the trace plots suggests that the aforementioned burn-in period is adequate and the chains are converged.

5.2. Parameter estimates and empirical findings

The estimates as well as their posterior means and 95% posterior intervals are reported in Table 3. The coefficients with star indicate that they are significant at the 95% level, as their respective 95% posterior intervals do not contain zero.

For parameters in donation rate (i.e., $\log(\lambda_i)$), we find that teacher-donors (i.e., *DonorIdentity*), their initial donation experiences with "donation gift card" program (i.e., *PaidbyGiftCard*) and "donation matching offer" program (including both "DYT" and "AH" matching offers) on DC.org have positive and significant effects on their donation rate. This suggests that (1) Compared with non-teacher donors, teacher-donors usually have higher willingness to donate; (2) Donors whose initial contribution involved with gift card and matching offer grants usually have more frequent donation performance. In other words, the two new marketing programs are indeed able to increase donors' contribution incidence. However, in our empirical results, *IsTeacherReferral* is found to have significant and negative impact (i.e., -0.4) on donors' donation rate. This indicates that compared with donors acquired from website visitors (i.e., site-donors), donors acquired through teacher referral intend to have lower donation tendency. This is reasonable because site-donors usually have stronger donation initiative and intend to make more frequent donation on the platform. However, donors referred by teachers usually have some specific donation motivations and are interested in some specific donation projects (for example, they may only care about the crowdfunding projects posted by the same teachers). Donors' initial contribution percentage (i.e., *DonPercentToDC*) to DC.org, their first successful donation results (i.e., *FundRaisingResult*) and "Thank-You" feedbacks (i.e., *IsThankUPacketRec*) from people who

⁶ <https://cran.r-project.org/web/packages/BayesianTools/vignettes/BayesianTools.html>

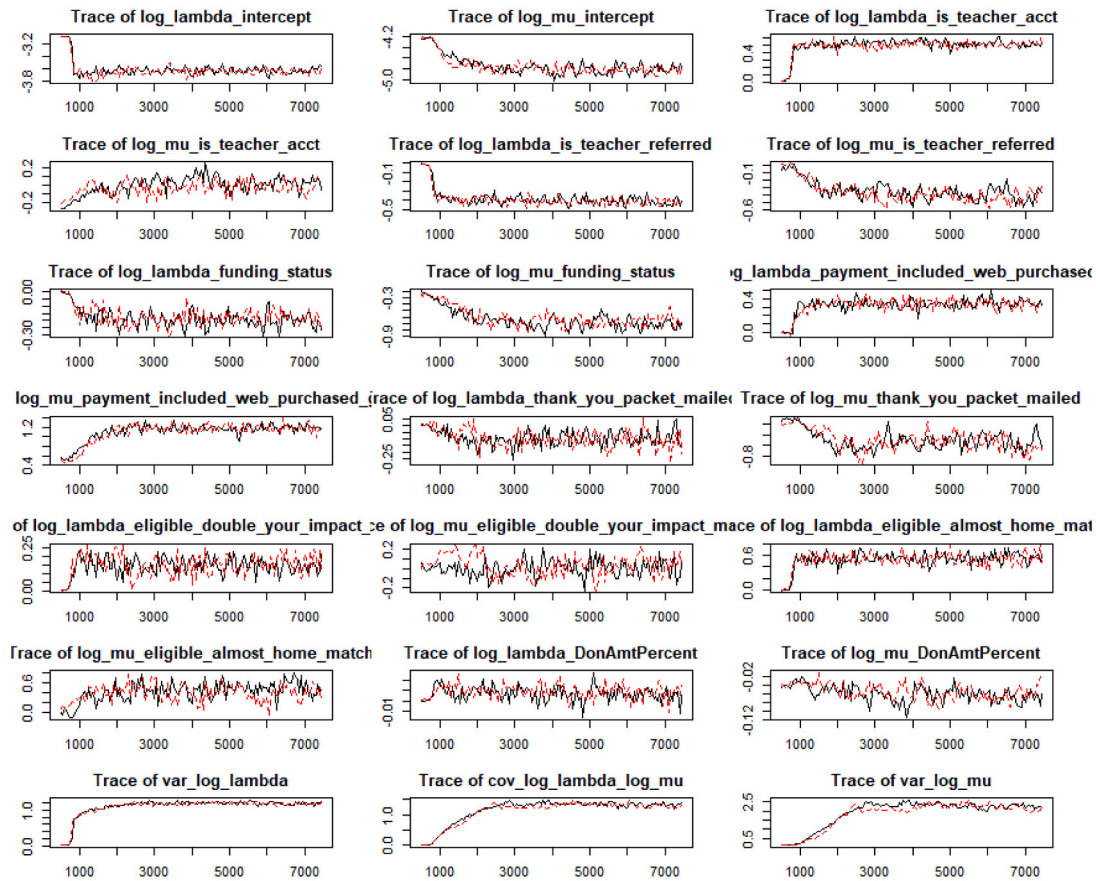


Figure 4. MCMC Trace Plot for All the Estimated Parameters

Fig. 4. MCMC Trace Plot for All the Estimated Parameters.

Table 3
Parameter Estimates.

Parameter	Posterior mean	95% Posterior Interval
Parameters in donation rate $\log(\lambda)$		
Intercept	-3.64*	(-3.73, -3.07)
DonorIdentity	0.51*	(0.03, 0.59)
IsTeacherReferral	-0.4*	(-0.49, -0.01)
DonPercentToDC	0.01	(-0.01, 0.02)
PaidbyGiftCard	0.32*	(0.01, 0.44)
DYIMatchingOffer	0.16*	(0.01, 0.24)
AHMatchingOffer	0.55*	(0.02, 0.71)
FundRaisingResult	-0.18	(-0.28, 0.01)
IsThankUPacketRec	-0.09	(-0.21, 0.01)
Parameters in dropout rate $\log(\gamma)$		
Intercept	-4.8*	(-4.98, -4.22)
DonorIdentity	-0.16*	(-0.3, -0.01)
IsTeacherReferral	-0.39*	(-0.58, -0.02)
DonPercentToDC	-0.06*	(-0.1, -0.03)
PaidbyGiftCard	1.15*	(0.56, 1.36)
DYIMatchingOffer	0.03	(-0.13, 0.19)
AHMatchingOffer	0.42*	(0.02, 0.75)
FundRaisingResult	-0.65*	(-0.85, -0.25)
IsThankUPacketRec	-0.52*	(-0.94, -0.16)
Covariance Matrix Σ		
σ_{λ}^2 : variance of $\log(\lambda)$	1.17*	(0.01, 1.24)
σ_{γ}^2 : variance of $\log(\gamma)$	2.21*	(0.15, 2.54)
$\delta_{\lambda\gamma}$: covariance	1.31*	(0.01, 1.45)

Notes: (1): Data in parentheses indicates the 2.5 and 97.5 percentiles;

benefit from the donation are found to have no significant influence on their donation rate in the platform.

For parameters in donation rate (i.e., $\log(\gamma_i)$), *PaidbyGiftCard* and *AHMatchingOffer* are found to have significantly positive influence (i.e., 1.15 and 0.42, respectively) on donors' attrition rate. However, *DonorIdentity*, *IsTeacherReferral*, *DonPercentToDC*, *FundRaisingResult* and *IsThankUPacketRec* are found to have negative and significant impact on donors' attrition rate. In other words, our empirical findings show that (1) Donors whose initial contribution involved with gift card and "AH" matching offer grants usually have higher attrition rate. In other words, donors, whose first donation is paid through gift card and matched by "AH" matching grant, usually have higher attrition rate. One possible explanation to this finding may come from the operation mechanisms of the two marketing programs on DC.org. In "donation gift card" program, all the gift cards have six-months expiration dates after the purchase date. If the gift card is unredeemed at the time of expiration, the funds will be applied to urgent classroom projects in need on the website. This operation rule encourages gift card recipients to redeem gift cards as soon as possible, and this may accelerate their attrition rate once the funds in the gift cards are used up. The "Almost Home" in the "donation matching offer" marketing program sounds like a coordination matching, in which the third foundations and corporations partner with DC.org will contribute part of the amount to crowdfunding projects as long as a specific fundraising purpose of the project is achieved. That is to say, the "Almost Home" matchers usually provide their funding gift conditional on other donors' contribution. Donors whose initial contribution is matched by "Almost Home" grant may give them an impression that the third party matchers will usually help the projects posted on the platform, and their help to the teachers are trivial. As such, they are more

likely to leave the platform. (2) More interesting, teacher-donors, donors achieved through teacher referral and donors who give more donation amount to *DC.org* at their initial contributions usually have lower attrition rate. (3) Donors' first successful donation result and "Thank-You" feedbacks from the people who benefit from the donation intend to decrease donor attrition rate on the platform.

By combining the empirical findings on donors' contribution and attrition behavior together, we are able to well disentangle the role of donation related covariates on their retention. The empirical results as a whole indicate that donors with teacher identity on *DC.org* usually have higher donation willingness and lower donation attrition rate. Although donors acquired through teacher referral have lower attrition rate, their donation rates are significantly lower than donors acquired from website visit. What interesting is that, the two marketing programs (i.e., "donation gift card" and "donation matching offer") on *DC.org* seem to be a double-edged sword to donor retention. On the one hand, the two marketing programs are found to have positive impact on donors' contribution rate. On the other hand, they are verified to be able to increase their dropout rate. However, donors' donation percentage to the platform, their successful initial contribution result and the "Thank You" feedbacks from people who benefit from their initial donations are found to have one-way impact on their retention behavior. That is because those factors are only found to exhibit significantly negative influence on donors' attrition rate, while their impact on donors' donation rate on *DC.org* is not significant. Finally, the estimated parameters from the covariance matrix Σ suggest that donors' donation behavior and attrition behavior are indeed significantly correlated (The estimated mean of correlation coefficient is 0.81). Donors with frequent previous donation on *DonorsChoose* platform intend to leave the platform.

(2): * indicates estimated coefficients significance at the 95% level;

6. Robustness checks

In this section, we conduct robustness checks to rule out alternative explanations for our model and empirical findings presented earlier.

6.1. Different donor cohorts

Although the donor cohort used in our main analysis is a full batch of donor samples from *DC.org*, they all come from the same group who have made their first-ever donation in the second quarter of 2013. Someone may argue that donors recruited at different time period may have different donation and attrition patterns. To exclude this possible contamination caused by donor sample selection, we re-collect two more cohorts of donors on the platform and examine their retention behavior with the same model. Specifically, we re-track all individual donors who made their first-ever donation in the first and third quarter of 2013 and had at least one donation record through September 2015 (the same end time as used in our main analysis). We name the donor group coming from the first and quarter of 2013 as "Donor Cohort A", and "Donor Cohort B", respectively.

Overall, there are 15,784 donors in "Donor Cohort A" and they have collectively made 97,467 donations and \$6,486,157 donation amount into 54,769 unique fundraising projects during our observation time period. "Donor Cohort B" comprises 22,230 donors who have totally made 208,723 donations and \$15,830,351 donation amount to 90,594 unique fundraising projects. Detailed information about the two donor groups are reported in Table 4. As we can see from this table, the average donation count (per donor) in cohorts A and B are 6.18 and 9.38, respectively, and the average donation amount (per donor) are 66.54 and 75.84, respectively. Donor cohort A has relatively lower average donation amount and count, while donor cohort B has relatively higher average donation amount and count. This small difference is understandable because different donors are included into those cohorts. In what follows, we are interested in whether those two donor cohorts

Table 4

Descriptive Statistics of the Selected Donor Cohort.

Descriptive statistics (Donation transaction level)	Donor cohort A	Donor cohort B
# Observations	97,467	208,723
# Donors	15,784	22,230
Mean Observation Per Donor	6.18	9.38
Average Amount Per Donation	\$ 66.54	\$75.84
Average Amount Per Donor	\$ 410.93	\$712.12

exhibit different retention behavior from our empirical findings.

We construct the same variables as those introduced in Section 3 for donor cohorts A and B, and calibrate the proposed model with those two groups of data sets by following the same steps as described in Section 4. The first and second panels of Table 5 report the posterior means and 95% posterior intervals for the parameter estimates from "Donor Cohort A" and "Donor Cohort B", respectively. As we can see from this table, donors' identity, acquisition channel and their initial donation experiences on *DC.org* all play the same roles as we find in our previous analysis. Therefore, the cross donor cohort analysis here verifies the robustness of our model and empirical findings.

6.2. Model validation and out of sample prediction

Thus far, we focus on explanatory results of our proposed model and

Table 5

Robustness Checks from Different Donor Cohorts.

Parameters	Donor Cohort A		Donor Cohort B	
	Mean	95% Interval	Mean	95% Interval
Parameters in donation rate				
$\log(\lambda)$				
Intercept	-3.85*	(-3.96, -3.26)	-3.77*	(-3.88, -3.14)
DonorIdentity	0.42*	(0.01, 0.49)	0.46*	(0.01, 0.52)
IsTeacherReferral	-0.38*	(-0.44, -0.01)	-0.31*	(-0.37, -0.01)
DonPercentToDC	0.01	(-0.01, 0.02)	0.01	(-0.01, 0.02)
PaidbyGiftCard	0.43*	(0.01, 0.51)	0.71*	(0.01, 0.8)
IsDYIMatchOffer	0.20*	(0.01, 0.26)	0.11*	(0.01, 0.16)
IsAHMatchOffer	0.37*	(0.01, 0.62)	0.56*	(0.01, 0.85)
FundRaisingResult	-0.05	(-0.14, 0.03)	-0.16	(-0.25, 0.01)
IsThankUPacketRec	-0.11	(-0.21, 0.01)	0.01	(-0.04, 0.08)
Parameters in dropout rate				
$\log(\gamma)$				
Intercept	-5.06*	(-5.28, -4.57)	-4.93*	(-5.12, -4.44)
DonorIdentity	-0.27*	(-0.40, -0.15)	-0.21*	(-0.37, -0.07)
IsTeacherReferral	-0.31*	(-0.45, -0.07)	-0.28*	(-0.40, -0.06)
DonPercentToDC	-0.09*	(-0.12, -0.04)	-0.04*	(-0.08, -0.01)
PaidbyGiftCard	1.28*	(0.65, 1.42)	1.81*	(0.84, 2.03)
IsDYIMatchOffer	0.09	(-0.06, 0.26)	0.03	(-0.02, 0.12)
IsAHMatchOffer	0.34*	(0.04, 0.72)	0.53*	(0.16, 0.76)
FundRaisingResult	-0.43*	(-0.61, -0.19)	-0.73*	(-0.90, -0.30)
IsThankUPacketRec	-0.33*	(-0.52, -0.06)	-0.23*	(-0.43, -0.10)
Covariance Matrix Σ				
σ_{λ}^2 : variance of $\log(\lambda)$	1.29*	(0.01, 1.36)	1.06*	(0.01, 1.13)
σ_{γ}^2 : variance of $\log(\gamma)$	2.26*	(0.01, 2.58)	1.87*	(0.09, 2.37)
$\delta_{\lambda\gamma}$: covariance	1.53*	(0.01, 1.68)	1.20*	(0.01, 1.38)

Notes: (1) Data in parentheses indicates the 2.5 and 97.5 percentiles; (2) * indicates estimated coefficients significance at the 95% level;

verify their robustness through different donor samples. Next, we turn our attention to the predictive capabilities of our proposed model and validate our empirical findings through out of sample prediction. To do this, we continue to track all the 9,255 donors' (i.e., the group of donors used in our main analysis) donation activities on *DonorsChoose* platform until October 2016. With the models and parameters estimated in Section 4, we predict each donor's donation activity between October 2015 and October 2016 based on their historical donation transactions in our observation time window (i.e., $[T_{\text{start}}, T_{\text{end}}]$). As a good way to assess the robustness and effectiveness of our model, we compare the predicted results with the real observed donation counts. The Mean Absolute Error (MAE) between the predicted values and real values is 1.05. Fig. 5 shows the distribution of the observed (solid black line) and predicted (dashed lines) number of donation across donors in the out of sample observation period. For the predicted donations, we report the results from three models: (1) full model including covariates, correlated donation rate and attrition rate (e.g., *FullModel*); (2) model only including correlated donation and attrition rate (e.g., *ModelWithCorrelatedRate*); and (3) model only including covariates (e.g., *ModelWithCovariates*).

As we can see from this Figure, all three models provide good predictions of the number of donations in the holdout period. It appears that the full model offers better prediction than other two models. This demonstrates our model's capability in capturing donors' donation behavior on the platform, and further verifies the robustness of our model.

7. Discussion and conclusion

Donor retention is a very important and urgent research topic for online charitable crowdfunding market. A key problem when studying this subject is donors' complex donation patterns. On the one hand, online donors usually have highly irregular donation timing and amounts. On the other hand, most of donors' online donation activities are usually characterized by latent attrition instead of observable churn behavior. Moreover, donors' attrition is usually correlated with their contribution. In this study, we decompose donor retention into two key

decision processes that a typical donor goes through (e.g., donation process and latent attrition process), and build up a structural model to jointly model both contribution and attrition behavior. To improve the proposed model's flexibility in fitting real operation scenarios of online charitable market, we allow donors' contribution rate and their latent attrition rate to be correlated and can be affected by donation related covariates.

By calibrating the proposed model with granular donation transaction data collected from different cohorts of donors on *DC.org*, our study shows that (1) Teacher-donors usually exhibit higher donation rate and lower dropout rate than normal donors; (2) Compared with site-donors, donors acquired through teacher referral usually have lower donation propensity and lower attrition rate; (3) From the perspective of donor retention, the "donation gift card" and "donation matching offer" prosocial programs provided by the platform seem to be a double-edged sword. Although they are found to have positive impact on donors' contribution rate, they are also verified to be able to increase donors' dropout rate; (4) Donors' donation amount to the platform, their successful initial donation result and the "Thank You" feedbacks from people who benefit from their initial donations can significantly decrease their attrition rate, but their impact on donors' contribution rate is not significant; (5) Donors' contribution behavior and latent attrition behavior are highly correlated, so we should not break them apart when examining their retention activities. A series of robustness checks are conducted to rule out alternative explanations for the aforementioned empirical findings. Our holistic model can be treated as benchmark when building more complicated model to disentangle donors' retention in online charitable crowdfunding. Furthermore, the proposed model can be generalized and modified to model customer retention in other online settings.

7.1. Managerial implications

Our study sheds light on practical implications for online charitable crowdfunding platforms, as well as many other offline non-profit organizations to improve their donor retention. For example, our study

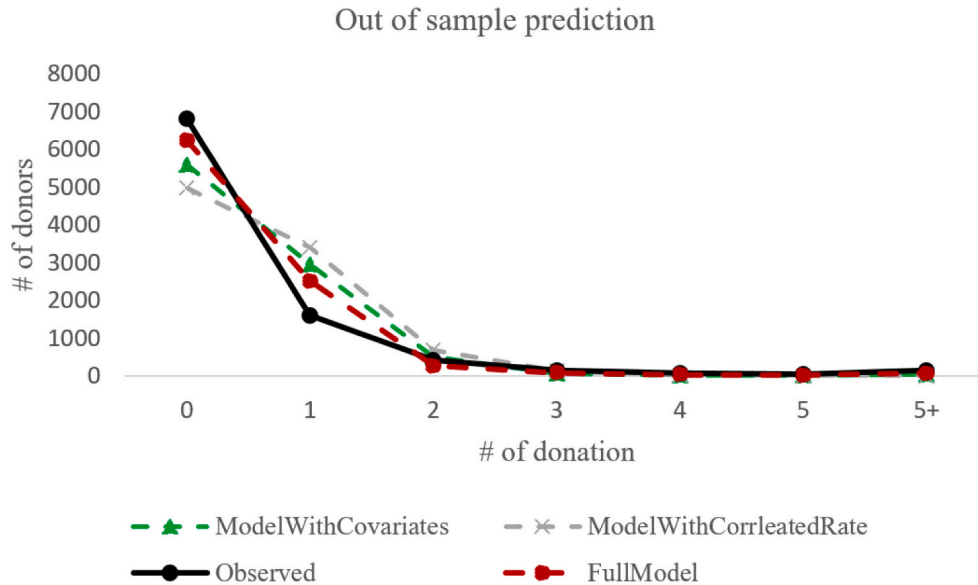


Figure 5. Model Validation Through the Perspective of Prediction

Fig. 5. Model Validation Through the Perspective of Prediction.

shows that donors with different identities (i.e., teacher-donors vs. normal donors) and acquired from varied channels (site-donors vs. teacher referral donors) usually have heterogeneous donation rate and attrition rate on the platform. Managers can make full use of this information and design more personalized donor acquisition and relationship management programs to cultivate their donors. Potential recommender systems in the online charitable market should also treat these donors differently when providing recommended projects list. Similarly, in our study, donors' initial donation percentage to the platform has been found to be a significant and important factor when predicting their latent attrition rate. This is valuable information for platform owners or charitable organizations to identify the donors who are more likely to leave the platform at their early "life time" and adopt some effective measures to retain them. Furthermore, our empirical findings show that the "donation gift card" and "donation matching offer" marketing programs on DC.org seem to be a double-edged sword. They are able to increase donors' donation propensity, at the same time, they can increase donors' attrition rate. Platform managers should take this into account and smartly use them by giving full play of their strong points to offset their weaknesses. Finally, online charitable platforms are suggested to add some new functions on their websites to celebrate donors' successful donation, especially donors' initial successful contribution on the platform. That is because donors' successful donation and the "Thank-You" feedbacks from fundraisers are found to be able to significantly decrease their attrition rate.

7.2. Limitation and future research

This study is subject to some limitations which point out our future research directions. First, the platform in our analysis is a classic education donation related platform, in which all donors make contributions to support public school classroom projects. There are many other types of non-profit platforms or organizations focusing on different causes such as virus and poverty fighting, water protection, and so on. Compared with DC.org, donors may change their contribution motivations when facing crowdfunding projects posted with varied causes. In this case, whether our empirical findings still hold in those new situations is a very interesting research question to be examined. In addition, due to data limitation, we only focus on the impact of covariates with strong theoretical or managerial importance (e.g., donors' identity, acquisition channels and initial donation experiences), we do not consider the possible influence from the interaction activities between donors and fundraisers. For example, online donors can participate in live projects' daily fundraising activities by posting comments or encouragement, and teachers can provide real time responses to donors. Both the quantity and quality of those activities may affect donors' donation and attrition behavior [25]. In future research, our model can be extended to incorporate this piece of information when it becomes available. Finally, additional marketing activities from platform can be collected to improve our understanding of donor retention [43]. We also believe how managers design more efficient new donor acquisition strategy and conduct donor relationship management with more granular online donation behavior is a fruitful area which warrants more research.

Acknowledgement

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